Are Arbitrageurs Less Affected by Behavioral Biases? Evidence from the Cryptocurrency Market

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Abstract

Behavioral biases are well-documented among less sophisticated investors. Are arbitrageurs less affected by these issues? To explore this question, we analyze account-level trading data from a leading cryptocurrency exchange in India and use triangular arbitrage opportunities to identify arbitrageurs and noise traders. While arbitrageurs outperform noise traders, we find that they are not immune to behavioral biases. In fact, arbitrageurs often exhibit higher levels of biases, and their returns are also more negatively impacted by a composite behavioral bias index than those of noise traders. Our results suggest that the classical rational assumption about arbitrageurs may be problematic when applied to newly emerged markets, such as cryptocurrencies, which could have important normative implications.

Keywords: bitcoin, cryptocurrency, behavioral biases, retail traders

JEL Codes:

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1. Introduction

Arbitrage is at the heart of modern finance. A large part of asset pricing theories builds on the seminar arbitrage pricing theory (APT) developed by Ross (1976), which articulates the expected returns of assets based on a no-arbitrage condition. When asset prices deviate from the APT, the premise is that arbitrageurs in financial markets will trade on these arbitrage opportunities and, by their trading, prompt asset prices back to their no-arbitrage equilibrium. Given the importance of arbitrageurs, vast efforts have been devoted to understanding the various types of frictions that these sophisticated investors may face, such as the short-selling constraints and noise trader risk (e.g., Miller 1977; Shleifer and Vishny, 1997; Gromb and Vayanos, 2010). Interestingly, much of the literature assumes that arbitrageurs are fully rational; hence the limits of arbitrage arise when these arbitrageurs face exogenous frictions such as noise traders with behavioral biases.

However, could arbitrageurs themselves be subject to behavioral biases? This question is important because their potential biases may significantly alter the traditional landscape of arbitrage and the limits of arbitrage. It is true that even sophisticated investors, such as mutual fund managers, may be subject to various biases and constraints.[1] However, affected fund managers often deliver poorer performance, making them less qualified under the classical definition of arbitrageurs—i.e., those who can make profits out of zero-cost and zero-risk arbitrage opportunities. In other words, the literature lacks direct evidence on whether affected investors engage in arbitrage and, perhaps more importantly, whether sophisticated investors exploiting arbitrage opportunities are less susceptible to behavioral biases.

Our paper aims to fill this economic void by providing some of the first evidence on the relationship between arbitrage and behavioral biases. To achieve this goal, we utilized a unique proprietary account-level dataset from a centralized cryptocurrency exchange in India. Our sample includes 605,848 randomly selected individual accounts trading more than 100 cryptocurrencies

[1] For instance, fund managers are subject to the disposition effect (e.g., Frazzini 2006; Cici 2012), overconfidence (e.g., Daniel et al., 1998; Baker et al., 2010), home bias (Coval and Moskowitz, 1999), and attention limitations (e.g., Kacperczyk et al. 2016)

during the period from March 2018 to March 2022. The benefit of exploring the cryptocurrency market is that there exist significant triangular arbitrage opportunities between crypto and fiat currencies (e.g., Dong and Dong, 2014; Smith 2016; Kroeger and Sarkar, 2017; Nan and Kaizoji, 2019; Kruckeberg and Scholz, 2020). But different from existing studies, we mainly use these triangular arbitrage opportunities to identify sophisticated investors who can exploit such opportunities—i.e., arbitrageurs.

Take an Indian investor who wants to buy Bitcoin as an example. The investor can use her local currency, Indian Rupee (INR), to buy Bitcoin directly. She can also first transfer her Rupees into US dollars and then use the US dollars to buy the same cryptocurrency. In theory, the two approaches should allow her to buy the same amount of cryptocurrency in the absence of transaction costs. In practice, however, the two approaches often yield very different results, indicating that the same cryptocurrency may have distinctive prices when purchased differently. This price difference illustrates a triangular arbitrage opportunity that can be utilized by arbitrageurs to make money. Our key intuition is that we can use the reveal preference approach to identify arbitrageurs based on the observed intensity of exploiting such opportunities.[2]

The above strategy allows us to identify arbitrageurs as follows. In each week, we calculate an *Arbitrage Score* (AS) for each investor in the past quarter (i.e., 13 weeks) as the trading volume of arbitrage-consistent transactions (i.e., trades in the same direction of triangular arbitrage) scaled by the value of the quarter-end holding balance.[3] We then sort investors into five groups according to the arbitrage score. When there is no confusion, we refer to investors within the quintile group of highest (lowest) *Arbitrage Scores* as arbitrageurs (noise traders). The distribution of arbitrage-consistent transactions, as captured by AS, is highly skewed among investors and concentrates among arbitrageurs. Roughly speaking, for every 1 INR in their balance, arbitrageurs' quarterly

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[2] When the two approaches imply different prices, a typical "triangular arbitrage" means buying the cryptocurrency using the cheaper-price approach and selling the cryptocurrency using the approach that implies a more expensive price. To make use of the triangular arbitrage opportunities, arbitrageurs need to have access to both the cryptocurrency and foreign exchange markets. This assumption is reasonable for the most sophisticated investors in India. At the minimum, sophisticated investors aware of triangular arbitrage should try to buy the cryptocurrency using a cheaper price to avoid being arbitraged.

[3] We calculate the account balance in Indian Rupee based on investors' order books and records of deposits and withdrawals. Since even random trading will assign a non-zero probability of arbitrage-consistent transactions, our main test focus on investors with non-zero *Arbitrage Scores*.

arbitrage-consistent trading volume amounts to 87.2 INR, compared to a trading volume of 0.123 INR among noise traders.

To set up the stage, we first investigate the most important premise of conducting arbitrage: to deliver risk-adjusted performance. To achieve this goal, we follow Barber and Odean (2000) to track the weekly account-level performance as holding-weighted returns of cryptocurrency portfolios. We then calculate the average out-of-sample weekly returns of investors within each AS quintile, and we rebalance the quintiles each week. In this portfolio analysis, we observe that arbitrageurs achieve the highest portfolio returns (5.7% raw, and 4.09% above the market). Furthermore, the weekly Sharpe Ratio of arbitrageurs (0.144) almost doubles that of the second-highest quintile (0.0729), which is still much higher than that of the noise traders (0.0188). Both portfolio returns and the Sharpe Ratio also monotonically increase in the *Arbitrage Scores* of investors. These observations collectively suggest that our *Arbitrage Scores* capture importance properties of sophisticated investors that can contribute to their performance.

Once receiving initial evidence on the performance of arbitrageurs, we proceed to investigate their behavioral biases. To achieve this goal, we also use the past-quarter information (i.e., the same period during which we compute the *Arbitrage Score*) to calculate four common types of behavioral biases for each investor: extrapolation, the disposition effect, lottery preference, and excessive trading (see, among others, Liao et al., 2022; Sui and Wang, 2023; Kumar 2009; Barber and Odean, 2000). For easy interpretation, we further consolidate these individual biases into a composite bias index, referred to as the *Composite Bias Score*, by summing the scaled levels of each bias. A higher level of behavioral bias, whether individual or reflected in the composite bias index, is negatively correlated with portfolio returns. This observation aligns with the behavioral literature and validates the interpretation of biases in our setup.

We then compute the average contemporaneous bias indices for each quintile of investors sorted by *Arbitrage Scores*. The striking observation is that, despite their sophistication and higher performance, arbitrageurs are not immune to behavioral biases. In fact, except for the disposition effect, arbitrageurs exhibit a higher level of bias in all the remaining three individual heuristics. As a result, arbitrageurs also receive a much higher level of the *Composite Bias Score* when compared to noise traders. Indeed, the average composite bias index increases *monotonically* with arbitrage score, suggesting that the observed high bias level of arbitrageurs reflects a general relationship between arbitrage and bias.

But if arbitrageurs exhibit a higher level of bias, shouldn't the latter negatively affect the performance of arbitrageurs? To address this issue, we independently double-sort investors into quintiles according to their *Arbitrage Scores* and the *Composite Bias Scores*. We first observe that, within each bias quintile, performance almost always monotonically increases in *Arbitrage Scores*. Economically speaking, this observation means that *Arbitrage Scores* still capture important sources of performance holding the level of bias constant.

The observations differ when we explore the impact of behavioral bias within arbitrage quintiles. Among high-arbitrage quintiles of investors, such as the top-quintile arbitrageurs, we observe that performance monotonically decreases in the *Composite Bias Scores*. Among arbitrageurs, the most biased significantly underperform the least biased by as high as 0.985% weekly returns. However, the bias impact on performance among noise traders becomes insignificant. Not only does the return spread between the most biased and the least biased noise traders become insignificant, we also fail to observe a monotonic bias-performance relationship.

To further verify the above return implication, we conduct pooled regression analysis at the account level to investigate how arbitrage and behavioral biases predict the out-of-sample portfolio returns of investors. The positive predicting power of *Arbitrage Scores* on weekly returns remains highly significant even after controlling *Compoite Bias Scores*, the characteristics of investor portfolios, as well as time and trader fixed effects. Alternative proxies of arbitrage, such as the rank of *Arbitrage Scores* and the dummy indicator for arbitrageurs, also exhibit significant return predicting power. On the other hand, both individual behavioral biases and the *Composite Bias Score* negatively predict returns.

We then investigate the impact of the interactions between *Arbitrage Scores* and the *Composite Bias Scores*. Consistent with our double-sorting results, the interaction predicts significantly negative returns. We further observe a significant coefficient for the interaction between the dummy indicator of arbitrageurs and that of the least bias, suggesting that unbiased arbitrageurs outperform other arbitrageurs. On the other hand, biased noise traders do not significantly underperform other noise traders.

Our conclusions remain highly robust using alternative arbitrageur measures and cutoffs, different portfolio return measures, and coin samples. In addition, we also observe that arbitrageurs tend to trade in higher volumes and hold fewer numbers of coins and that *Arbitrage Scores* are quite persistent. Indeed, the probability for an arbitrageur to remain in this position in the following week is 83.8%, compared to the almost negligible probability for her to transit to a noise trader (0.736%). Such persistence further suggests that our analysis may capture important features of arbitrageurs in the cryptocurrency market.

Overall, our results suggest that arbitrageurs are more biased than noise traders in the cryptocurrency market we investigate. The biases partially offset, but do not revert, the returns associated with *Arbitrage Scores.* The second result helps explain why profit-driven arbitrageurs may still exhibit return-damaging behavioral bias—the impact of behavioral bias may not be big enough on normal days to attract arbitrageurs' attention. However, this does not mean that a market with biased arbitrageurs will perform equally well as a market with fully rational arbitrageurs. Indeed, even without external frictions, the embedded behavioral bias of arbitrageurs may present a different type of limits to arbitrage by imposing constraints on market efficiency.

Our results are related to several strands of literature. We are first related to studies examining arbitrage in the cryptocurrency market, which document the prevalence of triangular arbitrage opportunities between bitcoin and fiat currencies as well as economic factors that influence the arbitrage opportunities across exchanges (Dong and Dong, 2014; Smith 2016; Kroeger and Sarkar, 2017; Nan and Kaizoji, 2019; Kruckeberg and Scholz, 2020; Makarov and Schoar, 2020; Choi et al., 2022). Different from these studies, we take the existence of triangular arbitrage opportunities as given and use them to illuminate important features of arbitrageurs at the account level.

Our analysis belongs to the emerging literature to examine the activities, preferences, and beliefs of cryptocurrency investors. A few studies use the leaked individual-level data of Mt.Gox, a Japanese bitcoin exchange that once dominated cryptocurrency trading but liquidated in 2014 (Gandal et al., 2018; Reynolds et al., 2021; Saggese et al., 2023). More recent studies use bank and credit card data to investigate the relationship between cryptocurrency transactions and consumption decisions (Aiello et al., 2023, 2024) and brokerage data to explore whether investors invest differently across stocks, gold, and cryptocurrencies (Kogan et al. 2024). In addition, cryptocurrency investors are also known to be sensitive to past performances, market sentiments, news, and other factors (Karaa et al., 2021; Grobys and Junttila, 2021; Almeida and Gonçalves, 2023; Anamika et al., 2023). We contribute by examining the performance and behavioral biases of arbitrageurs on cryptocurrency exchanges using a recent proprietary dataset. To the best of our knowledge, we provide the first direct evidence that arbitrageurs tend to exhibit higher levels of biases, which contradicts the classical rational assumption about these investors.

In doing so, we are also related to the literature on arbitrage and the limits of arbitrage. Existing studies typically emphasize the inefficient decisions made by noise traders (De Long et al., 1989; Shleifer and Summers, 1990; Shiller 2003). Our novelty is to show that, at least in the cryptocurrency market, arbitrageurs exhibit similar biases. Although these biases may not eliminate arbitrage profitability on normal days, they could present different types of limits to arbitrage to hamper market efficiency. Although sophisticated investors are known to exhibit various biases and constraints (among others, Frazzini 2006; Cici 2012; Daniel et al., 1998; Baker, et al., 2010; Coval and Moskowitz, 1999; Kacperczyk et al. 2016), the poor performance of these affected investors casts doubt on whether they engage in arbitrage. We contribute by providing direct evidence on the relationship between arbitrageurs and behavioral biases.

The rest of the paper is organized as follows. Section 2 defines the triangular arbitrage opportunities in the cryptocurrency market. Section 3 describes the data and the main variables. Section 4 analyzes the return, behavioral biases, and characteristics between arbitrageurs and noise traders. Section 5 focuses on subsamples and alternative measures. Section 6 concludes.

2. Triangular Arbitrage in Cryptocurrency Market

2.1 Background on cryptocurrency arbitrage

Triangular arbitrage is a trading strategy employed in the foreign exchange market to profit from pricing discrepancies among three different currencies. Frenkel and Levich (1975) studied triangular arbitrage opportunities as a proxy for transactions costs in the FX market: the upper limit of the costs should be the gap between the direct exchange rate of two currencies and the implied exchange rate derived from other currency pairs.

The essence of triangular arbitrage lies in the law of one price, though usually subject to transaction costs and regulatory restrictions (Pakko and Pollard, 2003). Given that triangular arbitrage opportunities among fiat currencies are rarely available (Rhee and Chang, 1992; Lyons and Moore , 2009), we focus on the less regulated cryptocurrency market, where we find persistent mispricing does exist.

In the cryptocurrency world, the existence of arbitrage opportunities across exchanges and regions are well documented. Dong and Dong (2014), Smith (2016) and Nan and Kaizoji (2019) identified that bitcoin-implied exchange rates deviate from nominal exchange rates. Similarly, Kroeger and Sarkar (2017) and Kruckeberg and Scholz (2020) both highlighted the significant differences in bitcoin prices among exchanges, while Makarov and Schoar (2020) documented larger price deviations of three most liquid coins across countries than within countries. Choi et al. (2022) pointed out that capital control explains the premium of bitcoin in the Korean market (also known as the Kimchi premium). In this paper, we examine the price inconsistency between the Indian and US cryptocurrency markets.

The leaked account-level data from the collapsed bitcoin exchange Mt.Gox has been used to explore the behavior of bitcoin traders. Gandal et al. (2018) identified suspicious trading activities and relevant profits on the exchange, while Chen et al. (2019) documented market manipulation patterns by certain important accounts. Saggese et al. (2023) demonstrated the existence of triangular arbitrage across all the three legs and the arbitrage profitability is associated with investors' trade ability and strategies. In this paper, we further explore the behavior and psychological biases of cryptocurrency investors using account-level trading data.

2.2 Setup of triangular arbitrage

India is one of the emerging market economies that adopt capital controls to maintain the stability of exchange rate and domestic credit market. Ostry et al. (2010, 2021) analyzed the rationale and policy implications behind the controlled capital flows in India. India's adoption of capital control has been in place as early as 1942. Currently, the government imposes restrictions on foreign exchanges for individuals, corporations and financial institutions (Patnaik and Shah, 2012). Indian capital controls set limitations on the amount of foreign currencies that can be brought, sent or lent abroad. With the rise of digital currencies, however, the cryptocurrency market offers a relatively frictionless way to transfer Indian rupee to other fiat currencies.

As shown in Figure 1(a), direct transfers between the Indian rupee and the US dollar is constrained, whereas transferring cryptocurrency such as bitcoin is less costly and unregulated. This regulatory difference creates a triangular arbitrage opportunity among cryptocurrencies and fiat currencies.

Taking the USD-BTC-INR pairs in Figure 1 as an example: Figure 1(a) illustrates the profitable flow when bitcoin is cheaper in the Indian market than in the US market, while Figure 1(b) shows the profit of arbitrage calculated step by step. When bitcoin is cheaper in India, investors can sell Indian rupee and buy bitcoin on the Indian exchange, then transfer the bitcoin to US. On the USD-based cryptocurrency exchanges, investors sell the bitcoin for US dollars. If the USD transferred through cryptocurrency markets exceeds the amount obtainable per Indian rupee through FX market, investors can profit from this arbitrage trade.

Specifically, if an investor holds one Indian rupee, she can purchase $\frac{1}{BTC/INR}$ amount of bitcoin on the Indian market. After transferring this amount of bitcoin to the US market, the investor could get $\frac{BTC/USD}{BTC/INR}$ amount of US dollars by selling the bitcoin. Given the bitcoin-impled exchange rate is higher than the real exchange rate, the investor profits by converting US dollars back to Indian rupees from the FX market. This process is shown in Figure 1(b), and the arbitrage profit calculated is later defined as the arbitrage index in Section 3.3.1.

<Insert Figure 1 here>

3. Data and Variables

3.1 Market Data

To analyze the triangular arbitrage opportunities on the Indian exchange, we require prices from three markets (as shown in Figure 1(b)): the Indian cryptocurrency market, the US cryptocurrency market and the FX market.

For prices on the Indian cryptocurrency market, we use daily closing prices from publicly available coin reports on the exchange's website. In addition to the fiat currency Indian rupee (INR), cryptocurrencies such as bitcoin (BTC) and tether (USDT) also serve as quote currencies. For coins quoted in BTC or USDT, we convert their prices into Indian rupee quoted at daily close.

We extract the prices of cryptocurrencies against the US dollar from CoinMarketCap, where daily closing prices, volumes and market caps are reported. Cryptocurrency markets operate 24/7 globally and follow the UTC time zone.

Overall, the trading history data includes 303 cryptocurrencies; among them 14 currencies are not covered by CoinMarketCap, and 4 currencies have unmatched time periods. Our subsequent calculation for cryptocurrency market return focuses on the sample of the 285 matched cryptocurrencies. A coin's circulating supply is defined as its total market cap divided by its closing price. Using data sourced from CoinMarketCap, which includes market cap (in USD) and closing price (in USD), we estimate the daily circulating supply for each cryptocurrency. We then multiply the circulating supply by the corresponding coin's closing price in Indian rupee to obtain the Indian rupee-quoted market cap and calculate the exchange level coin market return as the market-cap weighted coin returns.

The daily exchange rates between the Indian rupee and the US dollar are downloaded from Bloomberg. The FX market closes on Saturdays and Sundays but operates 24 hours a day on weekdays. In calculating the weekly triangular arbitrage index, we follow this schedule by setting Friday as the weekly close when the FX market closes.

3.2 Account Level Data

The unique proprietary data is sourced from a leading Indian cryptocurrency exchange, where more than 100 cryptocurrencies are traded. Investors can deposit and withdraw coins in and out of their wallets. We focus on the trading, deposit and withdrawal history of 605,848 randomly selected sample traders.

For each trade, we have detailed information on the IDs of the two trading parties, the quote and the base currencies, trading volumes, prices, fees and the fee currencies of each leg (details are shown in Table A1 in the appendix). We also have demographic information including the date of birth, gender, zip code and signup date for the sample traders as well as their trading counterparties (who are not necessarily sample traders). For the deposit and withdrawal data, we have the trader ID, currency, amount and direction variables.

In this paper, we focus exclusively on the cryptocurrency-Indian Rupee trading pairs to examine the triangular arbitrage opportunities in the cryptocurrency market. To ensure the presence of our sample coins in the U.S. market and rule out illiquid, small coins, our main sample includes the top 30 leading cryptocurrencies which account for more than 88% of the exchange's total trading volume. Since the Indian authority levied a capital gain tax on incomes from cryptocurrency transfers from April 2022, we limit our analysis to the pre-tax period from March 2018 to the end of March 2022.

Using the account-level trade data, we derive portfolio balances and calculate the trading implied returns for each account, following Barber and Odean (2000). As the exchange does not issue coin reports for all cryptocurrencies traded, we combine the closing prices from coin reports with data from our Trades files. For coins with official coin reports, we use the closing price documented in the reports; for those without, we take the price of the last trade every day as the daily closing price. Weekly portfolio return is defined as the holding-weighted average return of all coins held in the account, as in equation (1).

$$portfolio\ return_{i,t} = \sum_c \left(\frac{holding\ of\ coin\ c\ at\ week\ t-1}{total\ holdings\ at\ week\ t-1} \times return_{c,t} \right) \quad (1)$$

Besides, the Trades files also include the quoted currency and fee amounts on both the bid and ask sides. The fee rate is calculated as the amount of fee paid in INR scaled by the trade size in the same currency. The average fee rate in this exchange is around 0.003%.

3.3 Arbitrage Activity Related Variables

Following the discussions on the triangular arbitrage opportunities in Section 2, we construct several variables to measure the level of arbitrage opportunities in the market and arbitrage intensity for each account.

3.3.1 Arbitrage Index

The arbitrage index captures exchange-level triangular arbitrage opportunities owing to the divergence between cryptocurrency-implied exchange rates from real exchange rates. As indicated in Figure 1(b) and detailed in Formula (2) below, the arbitrage index measures the Indian rupee-quoted profit earned per 1 rupee put into triangular arbitrage, assuming no transaction and coin transfer costs.

$$\Delta_{c,t} = \frac{\frac{coin_c/USD}{coin_c/INR} - INR/USD}{INR/USD} \quad (2)$$

where INR/USD represents the closing exchange rate between US dollar and Indian rupee, $coin_c/USD$ and $coin_c/INR$ denote the coin closing prices quoted in US dollar and Indian rupee, respectively. A positive arbitrage index suggests that investors can arbitrage by buying cryptocurrency *c* and selling Indian rupee, while a negative arbitrage index indicates trades on the opposite direction.

Figure 2 illustrates the time-series change of USDT arbitrage index over the sample period. From Figure 2(a), we observe a substantial deviation in the price of USDT on the Indian exchange from that on US market, leading to an average absolute arbitrage profit of 0.0478 per rupee. The solid line represents the weeks when the arbitrage index is positive, and the dashed line stands for weeks with negative arbitrage index. In Figure 2(b), red line shows the tether(USDT) implied INR/USD exchange rate, which is more volatile compared to the real INR/USD exchange rate depicted in blue. The triangular arbitrage opportunities arise from the gap between the two lines.

3.3.2 Arbitrage Score

Despite fluctuations of the exchange-level arbitrage index, not all investors are sophisticated enough to fully exploit triangular arbitrage opportunities. We introduce a new variable: arbitrage score, to capture the extent to which an individual trader takes advantage of the arbitrage opportunities.

For each trader *i* conducting trade *j* on coin *c*, the arbitrage indicator defined in equation (3) specifies whether the trader's trading direction follows the arbitrage index in the previous week. For instance, if the arbitrage index of coin *c* in the previous week was positive, then we would assign every trade involving the purchase of coin *c* an indicator of 1, while each sale of coin *c* an indicator of 0.

$$arbitrage\ indicator_j = \begin{cases} 1, & if\ direction\ of\ trade\ j\ follows\ the\ arbitrage\ index\ of\ coin\ c \\ 0, & if\ direction\ of\ trade\ j\ does\ not\ follow\ the\ arbitrage\ index\ of\ coin\ c \end{cases} \quad (3)$$

In equation (4), we aggregate all trades of trader *i* in the past quarter (13 weeks) up to week *t* to calculate the arbitrage score variable. Arbitrage score measures the trading volume that investor *i* devoted to exploiting the triangular arbitrage opportunities in the past quarter scaled by account holdings at week *t*. A higher arbitrage score indicate more extensive arbitrage activities.

$$AS_{i,t} = \frac{\sum_j trade\ volume_j \times arbitrage\ indicator_j}{portfolio\ holding_{i,t}} \qquad (4)$$

3.4 Behavioral Biases Related Variables

Following previous literature on investor behavioral biases, we identify four behavioral biases that are applicable under the cryptocurrency setting: extrapolation, disposition effect, lottery preferences, and excessive trading. We calculate each individual bias measure at investor-week level, based on investors' trading activities in the past quarter. Subsequently, we aggregate these biases by ranking them every week to create the composite behavioral index (BI).

3.4.1 Extrapolation

Investors tend to overextrapolate from positive past returns. Following Liao et al. (2022), we measure the degree of extrapolation (DOX) by first determining the extrapolation indicator for each trade *j* conducted by investor *i*, as shown in equation (5). If investor *i* purchases coin with positive recent return in trade *j*, we assign this trade an extrapolation indicator of 1; otherwise a value of 0.

$$extrapolation\ indicator_{i,j} = \begin{cases} 1, & if\ trader\ i\ purchases\ coin\ with\ positive\ recent\ return \\ 0, & if\ trader\ i\ does\ not\ purchase\ coin\ with\ positive\ recent\ return \end{cases} \qquad (5)$$

We then aggregate all extrapolation trades of investor *i* in the past quarter to calculate the degree of extrapolation (DOX) at investor-week level. As indicated in equation (6), degree of extrapolation (DOX) equals to the fraction of extrapolating trade volume of investor *i* relative to her total trading volume.

$$DOX_{i,t} = \frac{\sum_j trade\ volume_{i,j} \times extrapolation\ indicator_{i,j}}{\sum_j trade\ volume_{i,j}} \quad (6)$$

3.4.2 Disposition effect

The disposition effect refers to investors' tendency to sell winners too quickly and hold losers for too long (Odean 1998). To examine the disposition effect, we first assess the capital gains and losses experienced by investors during their trading periods. For each investor in each week, if the closing price of a certain coin exceeds its average purchase price, it is classified as a capital gain; otherwise, it is considered a capital loss. The average purchase prices are calculated as the value-weighted average purchase price on the first-in-first-out basis for all the coins held in the account.

Then we estimate on model (7) following Sui and Wang (2023):

$$Sell_{i,c,t} = \alpha_{i,t} + \beta_{i,t} \times Gain_{i,c,t-1} + \epsilon_{i,t} \quad (7)$$

where $Sell_{i,c,t}$ is a dummy variable that equals 1 when investor *i* sells coin *c* in week *t*, and equals 0 when investor does not sell. $Gain_{i,c,t-1}$ is another dummy variable that equals to 1 when investor *i* experienced capital gain on coin *c* in the previous week. We run linear probability model to estimate equation (7). The estimated coefficient $\beta_{i,t}$ measures the disposition effect of investor *i* at week *t*.

3.4.3 Lottery preference

Individual investors prefer to buy lottery-like stocks. We follow Kumar (2009) to measure lottery-type features within our cryptocurrency context. We consider three dimensions for each coin: idiosyncratic volatility, idiosyncratic skewness and coin price.

At the end of each week, we calculate idiosyncratic volatility and idiosyncratic skewness using the cryptocurrency factor model from Liu et al. (2022), based on past 30 weeks' data. We collect the market, size and momentum factors in the cryptocurrency market from the author's website (www.yukunliu.com/research/). The idiosyncratic volatility and idiosyncratic skewness are calculated as the volatility and skewness of the residuals from the three-factor model.

Next, we sort the entire cryptocurrency sample by idiosyncratic volatility, idiosyncratic skewness, and coin price. And we define the lottery-like coins as those falling into the highest 50th percentile for idiosyncratic volatility, the highest 50th percentile for idiosyncratic skewness, and the lowest 50th percentile for price. The intensity of lottery preference for investor *i* at week *t* is measured as the percentage of lottery-type coins bought relative to total trading volume in the past quarter:

$$LP_{i,t} = \frac{\sum purchase\ amount\ of\ lottery - type\ coins}{\sum total\ trade\ volume} \tag{8}$$

3.4.4 Turnover

Individual investors tend to trade excessively, which can lead to underperformance (Barber and Odean 2000). The turnover variable captures the frequency of trading. As shown in equation (9), the portfolio turnover of investor *i* at week *t* equals to total trading volume in the past quarter, scaled by the portfolio balance at the end of the previous period.

$$turnover_{i,t} = \frac{total\ trade\ volume_{i,t}}{portfolio\ holding_{i,t-1}} \tag{9}$$

Table 1 reports the descriptive statistics of our key variables, following the calculations in Section 3. Our sample includes 30 cryptocurrencies with the highest trading volume and 213,084 traders engaged in transactions involving cryptocurrency-fiat currency pairs during the four-year sample period from March 2018 to March 2022.

All the arbitrage-related and bias-related variables are at investor-week level, while the demographic variables are at investor level. And all variables are winsorized.

<Insert Table 1 here>

4. Arbitrageurs versus Noise Traders: Empirical Evidence

This section examines the portfolio returns and behavioral bias levels of arbitrageurs in comparison to noise traders. We perform both portfolio sorting and pooling regression analyses to address the relationship between sophisticated trades like triangular arbitrage, and the psychological biases exhibited by traders.

4.1 Portfolio Analysis

To understand the features between arbitrageurs and non-arbitrageurs, we first categorize investors based on their arbitrage activities. Given that arbitrage scores are positively skewed, we exclude observations with no trades over one-quarter window and sort the remaining investor-week pairs into quintiles based on their arbitrage scores. Investors in the highest arbitrage score group arbitrage most extensively, and we label them as "arbitrageurs". Conversely, investors in the lowest group, who exhibit minimal arbitrage activities or trade in the opposite direction with the triangular arbitrage index, are labeled as "noise traders".

Table 2 reports the average portfolio performances and levels of behavioral biases of each investor group, sorted by arbitrage scores over the past quarter. Following the aforementioned classification, we define group 5, representing the highest arbitrage activities, as "arbitrageurs", while group 1, or "noise traders".

<Insert Table 2 here>

Panel A displays the weekly average portfolio performance for each sorted group, including trading implied portfolio return, market adjusted return and Sharpe ratio. The portfolio Sharpe ratio and skewness are calculated on a rolling basis. There exhibits a clear trend that the average portfolio returns increase monotonically as investors exploit more extensively on the triangular arbitrage opportunities. Arbitrageurs maintain superior performance after adjusting for market returns. Their portfolios are more volatile and skewed, yet still have higher Sharpe ratios compared with other groups. The results support the common belief that arbitrageurs, being more sophisticated informed, achieve better portfolio performance.

Panel B, however, reveals an intriguing pattern on trading behaviors across different groups. Among the four biases we adopt, arbitrageurs only exhibit a relatively lower level of the disposition effect, while score significantly higher in extrapolation, lottery preferences and excessive trading. Notably, arbitrageurs have the highest aggregate level of behavioral biases among all groups. This indicates that arbitrageurs, although more sophisticated, are not less immune to psychological biases. Despite their elevated level of biases, arbitrageurs still impressively outperform the other groups, with an average of 4.09% market adjusted return.

To further validate our finding, we independently sort all sample accounts into 25 portfolios by their aggregate arbitrage score and composite bias index. For each portfolio, we calculate the average weekly market-adjusted trading implied portfolio returns, with results reported in Table 3. We again label group 5 as "arbitrageurs" and group 1 as "noise traders". From column 1 to column 5 in Table 3, the average investors in the portfolios become more biased. We also report the differences between group 1 and group 5 as well as the t-statistics of the differences in return along both sorting dimensions.

<Insert Table 3 here>

As shown in Table 3, more biased investors generally achieve lower portfolio returns compared to their less biased counterparts, with arbitrageurs consistently outperforming noise traders across all scenarios. But the impact of behavioral biases varies across investors cohorts. Compared with groups that conduct less triangular arbitrage trades, the performance attributable to behavioral biases is significant among arbitrageurs: the difference in returns between the most biased and least biased arbitrageurs yields a t-statistic of -5.47, whereas for noise traders, the difference is insignificant with t-statistics at -0.95.

Arbitrageurs not only suffer from higher levels of behavioral biases but also exhibit a heightened sensitivity to overall behavioral biases, which significantly affects their performances. The same results also hold for trading implied returns and fee-adjusted returns. We also document the double sorting results on arbitrage score, composite bias index, account balance and weekly trading volume in the Appendix.

4.2 Pooled Regression Analysis

In this section, we examine the interaction between arbitrage trading and behavioral biases by running fixed-effect pooled regressions on our account-level panel data. First, we check whether arbitrageurs still outperform after controlling for the behavioral biases they face in their trading decision-makings. We then introduce different interaction terms to test the effects of arbitrage intensity, persistency and other characteristics of the arbitrageurs.

4.2.1 Baseline panel regression analysis

Previous analyses indicate that certain investors are effectively exploiting the triangular arbitrage opportunities on the Indian cryptocurrency exchange, yielding outstanding returns. We first run predictive pooled regressions on arbitrage-related variables and bias-related variables separately. The results presented in Table 4 further support our findings.

The following fixed effect regression model tests the relationship between the arbitrage activities and portfolio returns.

$$portfolio\ return_{i,t+1} = \alpha_{i,t} + \beta_{i,t} \times arbitrage\ score_{i,t} + controls + \epsilon_{i,t} \qquad (10)$$

The dependent variable $portfolio\ return_{i,t+1}$ represents the weekly trading implied portfolio return of investor i in week $t+1$. The key independent variable, $arbitrage\ score_{i,t}$, measures investor *i*'s arbitrage intensity within the prior quarter by week *t*. We also incorporate some alternative measures on arbitrage intensity. $rank_{i,t}$ reflects the rank of arbitrage score of investor *i* among all investors traded in week *t*. The dummy variable $arbitraguer_{i,t}$ is set to 1 if investor *i* is among the top 20% percentile for arbitrage trading at week *t*, while $noise\ trader_{i,t}$ is a dummy variable that equals 1 if investor *i*'s arbitrage score is in the bottom 20% percentile at week *t*. We control account-level characteristics include account balance, number of trades in the past quarter and number of currencies held in the account. We also control the investor and time fixed effects. The standard errors are robust to heteroskedasticity and clustered at investor level.

Similarly, we examine the influence of behavioral biases on market adjusted portfolio returns. In model (11), we test the impact of different bias-related variables: extrapolation, disposition effect, lottery preference, turnover and the composite bias index.

$$portfolio\ return_{i,t+1} = \alpha_{i,t} + \beta_{i,t} \times behavioral\ bias_{i,t} + controls + \epsilon_{i,t} \qquad (11)$$

Table 4 presents the baseline results: panel A focuses on the regressions on arbitrage intensity, and panel B displays the regressions on behavioral biases. The intensity of arbitrage is a positive predictor of portfolio returns, while all behavioral biases negatively predict portfolio return. The findings are consistent with the common beliefs that arbitrageurs make higher profits and behavioral biases are harmful to investment performance.

<Insert Table 4 here>

4.2.2 Are arbitrageurs more biased?

Previous studies on investment behavioral biases predominantly focus on retail investors who are less informed (Odean 1998, Odean 1999, Barber and Odean 2000, Barber and Odean 2001). More sophisticated investors, mainly institutional investors including mutual funds and hedge funds, suffer from psychological biases but are less exposed compared to individual investors (Grinblatt and Keloharju (2011), Kumar (2009), Bailey et al. (2011), Cici (2012)). In this section, we test whether sophisticated arbitrageurs are less biased.

In model (12) we test the performance of arbitrageurs after controlling for their behavioral biases.

$$portfolio\ return_{i,t+1} = \alpha_{i,t} + \beta_{i,t} \times arbitrage\ score_{i,t} + \gamma_{i,t} \times behavioral\ bias_{i,t} + controls + \epsilon_{i,t} \quad (12)$$

The dependent variable $portfolio\ return_{i,t+1}$ represents the weekly trading implied portfolio return of investor *i* in week *t+1*. The key independent variable $arbitrage\ score_{i,t}$ measures investor *i*'s arbitrage intensity within the prior quarter by week *t*. We control for the individual behavioral biases and the composite bias index. We also use the alternative measures for arbitrageurs$rank_{i,t}$ reflects the rank of arbitrage score of investor *i* among all investors traded in week *t*; the dummy variable $arbitraguer_{i,t}$ is set to 1 if investor *i* is among the top 20% percentile for arbitrage trading at week *t*; while $noise\ trader_{i,t}$ is a dummy variable that equals 1 if investor *i*'s arbitrage score is in the bottom 20% percentile at week *t*. We control the account-level characteristics, investor and time fixed effects. The standard errors are robust to heteroskedasticity and clustered at investor level.

We again run the fixed effect pooled regression for model (12) and report the results in Table 5. After controlling their behavioral biases, arbitrageurs still significantly outperform other investor groups. In column (1) through (5) where we control for individual biases, the coefficients on arbitrage intensity and arbitrageur variables are all significant and positive. Specifically, a one standard deviation increase in arbitrage score implies a 0.54% increase in weekly portfolio performance. In column (6) to (10), we control for the composite bias index and get similar results.

<Insert Table 5 here>

To further examine the relationship between the participation of arbitrage trades and behavioral biases, we run the following regressions with investor and time fixed effects:

$$\begin{aligned} portfolio\ return_{i,t+1} \\ &= \alpha_{i,t} + \beta_{1i,t} \times arbitraguer_{i,t} + \beta_{2i,t} \times noise\ trader_{i,t} \\ &+ \beta_{3i,t} \times unbiased_{i,t} + \beta_{4i,t} \times biased_{i,t} \\ &+ \beta_{5i,t} \times arbitraguer_{i,t} \times unbiased_{i,t} + \beta_{6i,t} \times noise\ trader_{i,t} \times unbiased_{i,t} \\ &+ controls + \epsilon_{i,t} \qquad (13) \end{aligned}$$

where $portfolio\ return_{i,t+1}$ represents the weekly trading implied portfolio return of investor *i* in week *t+1*. We include two groups of dummy independent variables: $arbitraguer_{i,t}$ is a dummy variable that equals 1 if investor *i*'s arbitrage activity falls into the top 20% percentile, while $noise\ trader_{i,t}$ is a dummy variable that equals 1 if the arbitrage score of investor *i* belongs to the bottom 20% percentile. We try three different percentile pairs for the $unbiased_{i,t}$ and $biased_{i,t}$ dummies. For the 20-80 cutoff: $unbiased_{i,t}$ equals 1 if investor *i*'s composite bias index belongs to the bottom 20% percentile, while $biased_{i,t}$ is a dummy variable that equals 1 if the composite bias index of investor *i* is in the top 20% percentile. We also regress on the 33-66 cutoff, 40-60 cutoff and absolute score values of arbitrage score and composite bias index. The regression results are shown in Table 6.

<Insert Table 6 here>

The coefficient $\beta_{5i,t}$ reflects the relative performance of unbiased arbitrageurs, and coefficient $\beta_{6i,t}$ measures the relative portfolio return of biased noise traders. In columns (1), (3), (5) and (7), we have consistent results that arbitrageurs outperform while biased traders underperform. Interaction terms are added in columns (2), (4), (6) and (8). Among all our tested cutoffs, $\beta_{5i,t}$ is positive and significant, compared to the less significant and non-negative $\beta_{6i,t}$. The results here further support our conclusion from Table 3: unbiased traders significantly outperform among arbitrageurs, but for noise traders, behavioral biases do not have such detrimental impact on portfolio returns. And similar results emerged for different cutoffs.

4.2.3 Features of arbitrage trading

In this section we investigate the persistence of investors' trading styles. We employ the transition matrix, which is widely used in credit risk analysis, to demonstrate the probabilities that investors in one group transiting to another group in the subsequent period.

For each week, we calculate the transition rate from group *i* to group *j* using the following formula:

$$transition\ rate_{ij} = \frac{p_{ij}}{p_i} \qquad (14)$$

where p_i represents the total number of traders in group *i* at the beginning of the week, and p_{ij} denotes the number of traders that transfer from group *i* to group *j* during the week. The transition rates measure the probability that investors in group *i* move into group *j* over one period.

Meanwhile, $transition\ rate_{ii}$ represents the probability that investors in group *i* remain in the same group from one week to the next. The transition matrix is presented in Table 7. Each cell within the matrix indicates the average weekly transition rate from one group to another. The vertical serial number corresponds to the group that the investor belongs in the past week, and the horizontal axis denotes the group that investor turns into in the new week.

<Insert Table 7 here>

For a noise trader, the probability of remaining as a noise trader in the next period is more than 0.89, compared to the 0.007 likelihood that a noise trader transfers to an arbitrageur in one week. Similarly, 83.8% of arbitrageurs remain as arbitrageurs in the next week, with only 1.79% of them switching to noise traders. The transition matrix indicates that our sample cryptocurrency traders are consistent in their trading strategies.

Given this persistence in trading behavior, we take a closer look at the characteristics of the arbitrageurs' accounts. The AS_count_i variable measures the frequency that account *i* is classified as an "arbitrageur" throughout its trading history. AS_count_i is defined as the number of times that investor *i* has an arbitrage score that falls into the top 20% percentile over the total number of weeks that investor *i* traded in the past quarter.

We sort all sample investors into five groups by their frequency of being classified as arbitrageurs, and the characteristics are displayed in Table 8.

<Insert Table 8 here>

Investors in the highest frequency group are, on average, categorized as arbitrageurs 95% of their trading periods, as opposed to the 3% frequency among the first group. Investors who arbitrage more frequently tend to have higher trading volumes, fewer account holdings, leading to elevated turnovers. Arbitrageur accounts also hold fewer variety of currencies and, not surprisingly, exhibit higher aggregate level of behavioral biases.

5. Robustness Check

In this section, we perform robustness tests to validate our results. We run three sets of robustness checks on alternative arbitrage measures, return measures and coin samples.

We first apply an alternative arbitrage measure, high-intensity arbitrage score, as an alternative classification for arbitrageurs and noise traders. In the previous section, we only consider the direction rather than the magnitude of arbitrage opportunities. We define the high-intensity arbitrage events as weeks in which arbitrage scores that fall into the top and bottom 25th percentiles. Only trades conducted in the same direction with the arbitrage scores under the high-intensity arbitrage events are assigned 1 for the arbitrage indicator. The high-intensity arbitrage score ($ASH_{i,t}$) for trader *i* at week *t* is then calculated as the percentage of high-intensity arbitrage volume over total trading volume in the past quarter. We rerun the double sort analysis in Table 3 and the panel regression model in Table 5 using this alternative arbitrage intensity measure, with the results reported in Table 9. Panel A displays the market-adjusted portfolio returns sorted independently by high-intensity arbitrage score and composite bias index. Panel B shows the fixed-effect panel regressions on portfolio implied return. Our findings remain consistent, reinforcing our previous conclusions.

Secondly, we consider alternative return measures. In addition to the market-adjusted trading implied portfolio return used in our main analysis, we also examine the raw trading implied return and fee-adjusted trading implied return. The fee-adjusted trading implied return is calculated by deducting the total trading fee paid in the week (converted to Indian Rupee) from the weekly trading implied return, scaled by portfolio holing. The average trading fee is low at only 0.003% fee rate per trade in the Indian cryptocurrency exchange. The results of the double sort and pooled regression on fee adjusted portfolio returns are reported in Table 10, and remain consistent with our previous findings.

Lastly, we check whether different cryptocurrency samples affect our findings. In our primary sample, we focus on the top 30 cryptocurrencies with the highest trading volume. Here we rerun our main tests in Table 5 and Table 6 on alternative coin samples and report these robustness checks in Table 11. Our main findings hold when we turn to the top 10 and top 20 cryptocurrencies sample, as well as a sample that excludes the least traded 20% of cryptocurrencies.

6. Conclusion

This paper mainly examines the behavior of arbitrageurs and non-arbitrageurs from the perspective of behavioral biases in the cryptocurrency market. With the persistent triangular arbitrage opportunities and proprietary data from an Indian cryptocurrency exchange, we document the significant outperformance of arbitrageurs compared to noise traders, along with a higher level of behavioral biases affecting arbitrageurs in their trading activities. Our findings are contributive and surprising, challenging the common assumption that sophisticated investors who exploit arbitrage opportunities in financial markets should be less prone to biases. Our empirical analysis implies that arbitrageurs' investment returns are more sensitively impacted by behavioral biases including overextrapolation, the disposition effect, lottery preference and excessive trading.

We empirically explore the behavioral biases of cryptocurrency investors using account-level trading data. First, we introduce the arbitrage score to quantify the arbitrage activities taken by each trader and aggregate the composite bias index to count for the overall behavioral bias level faced by investors through their trades. We find out that arbitrage activities positively predict portfolio return, while behavioral biases negatively predict portfolio return. Second, even after controlling behavioral biases, arbitrageurs continue to outperform, although the impacts of behavioral biases are different among different groups of traders. Compared to noise traders, arbitrageurs' returns are more negatively affected by the behavioral bias they experience. Furthermore, the trading patterns of both arbitrageurs and noise traders are persistent, which further validates our findings.

Our results suggest that arbitrageurs, despite their sophistication in trading and potential access to more information, are not immune to behavioral biases.

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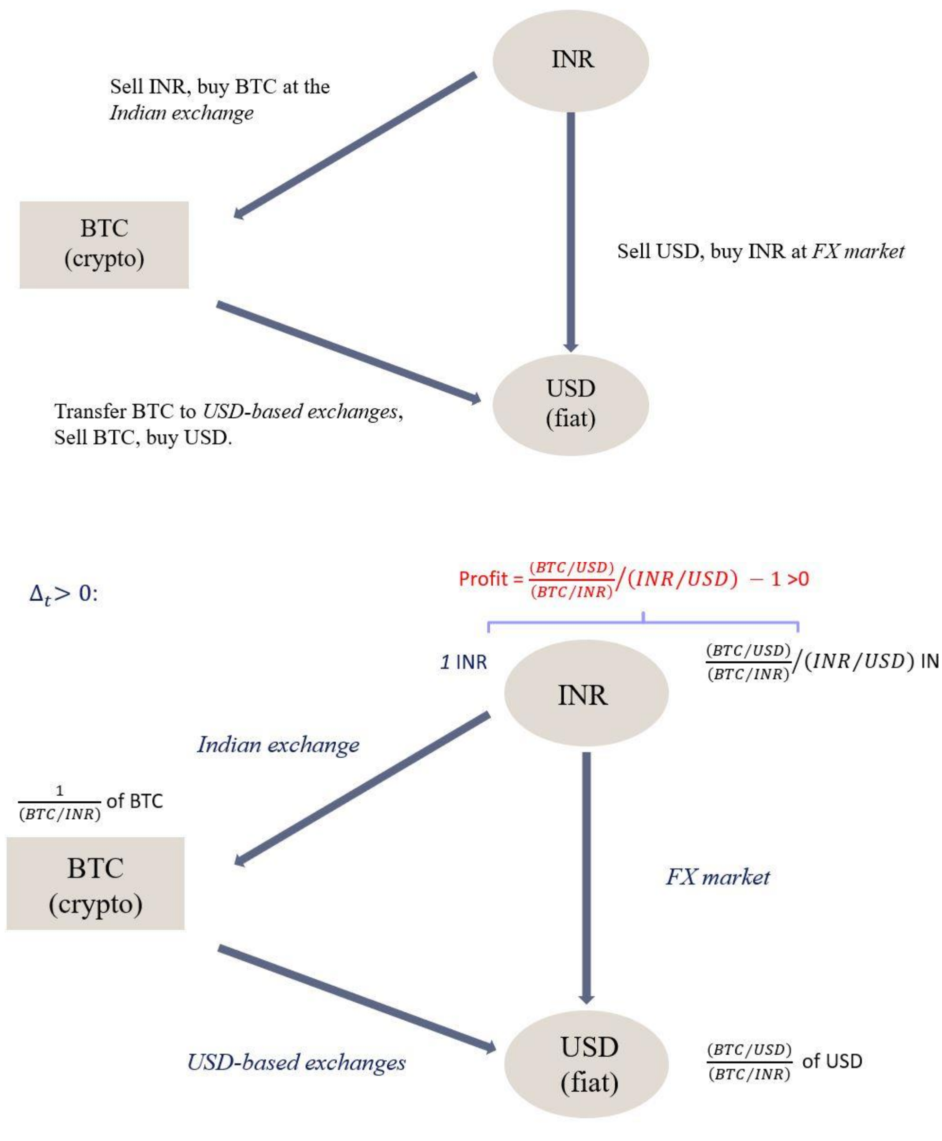
Figure 1: Triangular arbitrage in cryptocurrency market: bitcoin as an example

This figure sketches the potential triangular arbitrage opportunities using Bitcoin. If the bitcoin is cheaper at Indian market than at US market (that is, the arbitrage index is positive), investors could profit by buying bitcoin at the Indian exchange and selling bitcoin at USD-based exchanges.

(a) Triangular arbitrage in cryptocurrency market (USD-BTC-INR)

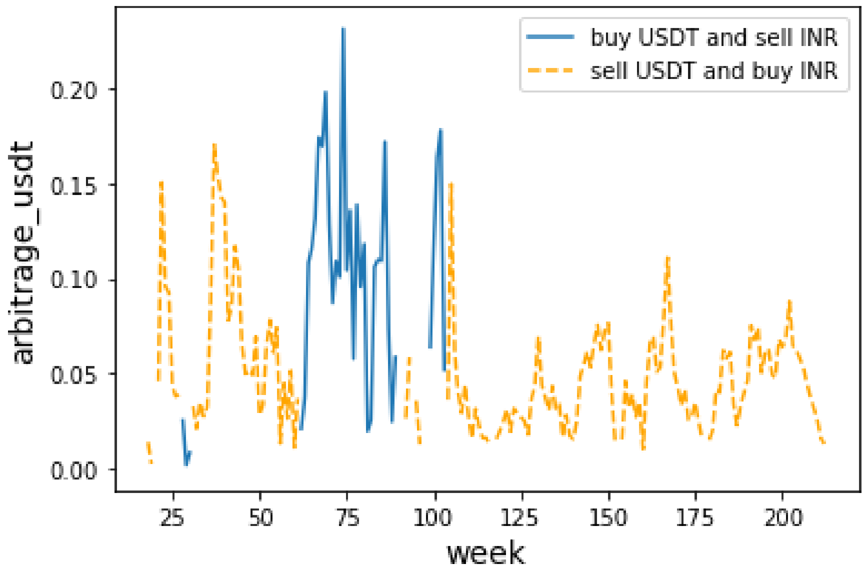


(b) Potential triangular arbitrage profits (USD-BTC-INR)

Figure 2: USDT arbitrage index

Figure (a) shows the weekly level of USDT arbitrage profit (in INR). The blue part indicates the positive arbitrage index: arbitrageurs could profit by buying USDT at Indian market; while the orange part represents the negative arbitrage index: arbitraguers could benefit from selling USDT at Indian market. Figure (b) shows the source of triangular arbitrage opportunities: the divergence of cryptocurrency-implied exchange rate from the real exchange rate. The absolute distance between the blue line and the red line indicates the level of arbitrage opportunities in figure (a).

(a) Time series USDT arbitrage profit (in INR)



(b) Real exchange rate versus USDT implied exchange rate

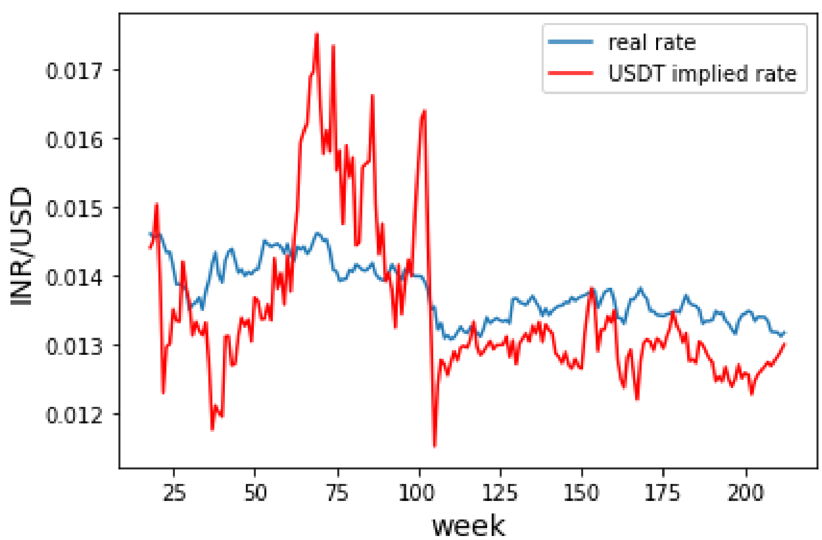


Figure 3: Overall arbitrage opportunities

This figure shows the market cap weighted arbitrage index of the leading 30 cryptocurrencies on WazirX. The red line indicates the weekly average fee rate that is calculated trade-by-trade as the proportion of trading fee (in INR) over trading volume (in INR).

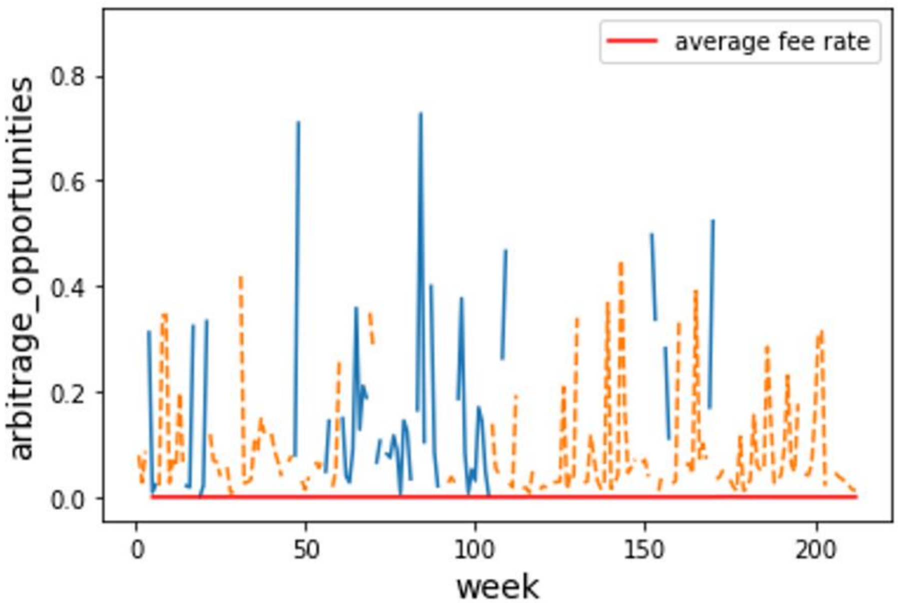


Table 1: Summary Statistics

This table reports the descriptive statistics for arbitrage- and behavioral bias- related variables. Our sample include 213,084 traders that had traded one of the top 30 cryptocurrency-INR pair during the time period: March 2018-March 2022.The trading implied portfolio returns are calculated on weekly basis, while the traders' arbitrage activities and behavioral biases are calculated every week based on their trades in the past quarter. AS (quarter) and rank_as are arbitrage score and rank of arbitrage score of each investor of every trading week. The weekly portfolio market adjusted return is calculated as the trade implied return extracted by market return. DOX, DE, LP and Turnover are the level of extrapolation, disposition effect, lottery preference and turnover based on the past one quarter's trading activities.

	N	mean	std	P25	median	P75	P90
AS (quarter)	4,316,120	19.33111	49.08802	0.395767	1.559093	7.402767	49.1863
rank_as	4,316,120	0.500025	0.288675	0.250025	0.50002	0.750021	0.900026
Weekly trade implied return (%)	2,141,001	5.1669	0.225949	-3.858	0	5.3109	28.3329
Weekly market adjusted return (%)	2,141,001	3.317	0.214142	-7.556	-1.327	6.2424	21.9766
Weekly market return (%)	214	1.3505	0.07	-3.231	0.7283	5.6044	12.3055
DOX (quarter)	4,311,205	4.350046	10.83508	0	0.455535	1.983958	11.00142
DE (quarter)	2,595,470	0.17473	0.349976	0	2.05E-17	3.33E-16	1
LP (quarter)	4,311,205	0.420945	0.389707	0	0.394893	0.785464	1
Turnover (quarter)	4,205,612	8.529076	20.65263	0	0.962821	4.442767	22.09247
log account balance	4,212,371	9.421252	2.662328	7.879405	9.72253	11.22489	12.53701
Quarterly number of trades	4,316,120	62.98977	175.0903	7	19	55	142
Number of currencies held	4,311,205	3.078019	1.13278	2.235294	2.791667	3.619048	4.857143
Age	605,848	31.83	9.12	25	30	37	45
Gender	605,848	0.81	0.39	1.0	1.0	1.0	1.0
Local	605,848	0.71	0.45	0.0	1.0	1.0	1.0
Weeks_since_joining	4,255,207	68.62	55.93	22	54	112	156

Table 2: Arbitrageurs versus Noise traders: single sort evidence

This table reports the single sort results by arbitrage score. The arbitrage score is defined as the trading volume that tries to exploit the triangular arbitrage opportunities taken by investor *i* in the past quarter scaled by account holdings at week *t*. Panel A shows the average portfolio performance of each group, while panel B displays the levels of behavioral biases each group face. In each panel, group 5, which arbitrage most intensively among all traders, are considered as "arbitrageurs", while group 1 traders are labelled as "noise traders". All variables are calculated at investor-week level.

Panel A: portfolio performance						
rank	AS_agg	Trading implied return (%)	Market adjusted portfolio return (%)	Sharpe ratio	Standard deviation	Skewness
1	0.123082	4.836066	2.995104	0.018798	0.140765	0.119342
2	0.613838	4.878025	3.014365	0.027566	0.140548	0.128095
3	1.779395	5.153114	3.189306	0.040406	0.148920	0.142716
4	6.934573	5.272874	3.340729	0.072929	0.156786	0.159543
5	87.200680	5.699942	4.094517	0.144059	0.182409	0.155041

Panel B: behavioral biases						
rank	AS_agg	Extrapolation	Disposition Effect	Lottery preference	Turnover	Composite bias index
1	0.123082	1.968569	0.195598	0.352163	3.241812	10.75643
2	0.613838	2.73523	0.187767	0.432117	5.252467	11.82434
3	1.779395	3.822558	0.185343	0.456613	7.502241	12.5997
4	6.934573	5.438575	0.162933	0.461524	10.61709	13.32286
5	87.200680	7.786493	0.151195	0.402326	16.01289	13.77405

Table 3: Market adjusted portfolio returns by arbitrage activity and composite bias index

This table reports the weekly market adjusted portfolio returns of the 25 portfolios sorted independently by arbitrage score and composite bias index. Traders are assigned to one group each week based on their arbitrage activities and behavioral bias level in the past quarter. The portfolio return is calculated as the weekly holding weighted coin returns of each account, adjusted by the market return at the local exchange. We also calculate the differences between group 5 and group 1, that are, the return differences between arbitrageurs and noise traders, and between biased investors and unbiased investors. t-statistics are reported in parentheses.
This table clearly shows that arbitrageurs always receive significantly higher returns than noise traders, yet the compounded level of behavioral biases tends to impose higher influence among arbitrageurs compared to noise traders.

TIR (%)	rank_bs	1	2	3	4	5	5-1
rank_as							
1		2.597449	2.027391	2.302755	2.138154	2.38936	-0.20809 (-0.95)
2		2.303891	2.392085	2.167434	2.378936	2.414544	0.110653 (0.49)
3		3.048455	3.148812	3.205526	3.065703	2.788222	-0.26023 (-5.98)
4		3.206022	3.275387	3.331828	3.240261	3.034895	-0.17113 (-8.12)
5		4.736931	4.197224	4.071108	3.962064	3.751594	-0.98534 (-5.47)
5-1		2.139482 (18.03)	2.169834 (14.90)	1.768353 (14.71)	1.82391 (15.69)	1.362234 (11.54)	

Table 4: Baseline panel regressions on arbitrage score and behavioral biases

This table reports the pooled regression estimates of weekly portfolio returns on arbitrage-related variables and behavioral bias variables. Panel A shows the results of regressing weekly portfolio returns on the arbitrage activities in the past quarter. *rank_as* is the rank of arbitrage score (AS), while *arbitrageur* and *noise trader* are dummies when certain traders fall into the top and bottom 20% on arbitrage score (AS). Panel B shows the results of regressing weekly portfolio returns on four behavioral biases and the composite bias index, calculated based on the trading history in the past quarter. We control for both time fixed effect and trader fixed effect, all standard errors are clustered at trader level. t-statistics are reported in parentheses and the superscripts of *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: regressions on arbitrage score

	Market adjusted trading implied return (week)				
	(1)	(2)	(3)	(4)	(5)
AS	0.0000940***				
	(15.97)				
rank_as		0.0115***			
		(12.99)			
arbitrageur			0.00870***		0.00874***
			(15.71)		(15.77)
noise trader				0.000185	0.000677
				(0.38)	(1.40)
balance	-0.00451***	-0.00466***	-0.00458***	-0.00494***	-0.00459***
	(-32.28)	(-33.37)	(-32.86)	(-35.68)	(-32.87)
trade_num	-0.00000528***	-0.00000510***	-0.00000558***	-0.00000135	-0.00000547***
	(-5.20)	(-4.89)	(-5.38)	(-1.37)	(-5.25)
currency_num	-0.00603***	-0.00629***	-0.00611***	-0.00593***	-0.00609***
	(-16.47)	(-17.11)	(-16.68)	(-16.20)	(-16.60)
FE	Yes	Yes	Yes	Yes	Yes
N	2,037,878	2,037,878	2,037,878	2,037,878	2,037,878
Adj R^2	0.196	0.196	0.196	0.196	0.196

Panel B: regressions on behavioral biases

	Market adjusted trading implied return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
DOX	-0.000101***				-0.0000701***	
	(-5.54)				(-2.74)	
DE		-0.00113			-0.000950	
		(-1.15)			(-0.96)	
LP			-0.00351***		-0.00200***	
			(-6.62)		(-2.93)	
Turnover				-0.0000690***	-0.0000531***	
				(-7.37)	(-4.20)	
Aggregate bias score						-0.000477***
						(-5.94)

FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2,037,878	1,420,219	2,037,878	1,374,607	1,374,607	1,420,219

Table 5: Panel regression analysis

This table reports the pooled regression estimates of weekly portfolio returns on arbitrage-related variables when controlling for behavioral biases as well as the composite bias index.

$$portfolio\ return_{i,t+1} = \alpha_{i,t} + \beta_{i,t} \times arbitrage\ score_{i,t} + \gamma_{i,t} \times behavioral\ bias_{i,t} + controls + \epsilon_{i,t}$$

We control for both time fixed effect and trader fixed effect, all standard errors are clustered at trader level. After adding behavioral bias variables as controls, arbitrage score (AS) still positively predicts the market adjusted portfolio returns. t-statistics are reported in parentheses and the superscripts of *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	Market adjusted trading implied return (week)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AS	0.000110***					0.000109***				
	(14.36)					(14.29)				
rank_as		0.0128***					0.0135***			
		(10.84)					(11.31)			
arbitrageur			0.00791***		0.00790***			0.00799***		0.00797***
			(11.94)		(11.92)			(12.05)		(12.03)
noise trader				-0.000547	-0.000281				-0.000743	-0.000518
				(-0.85)	(-0.44)				(-1.15)	(-0.80)
DOX	-0.0000786***	-0.0000817***	-0.0000780***	-0.0000704***	-0.0000781***					
	(-3.07)	(-3.19)	(-3.04)	(-2.75)	(-3.05)					
DE	-0.000465	-0.000213	-0.000443	-0.000926	-0.000431					
	(-0.47)	(-0.21)	(-0.45)	(-0.93)	(-0.43)					
LP	-0.00215***	-0.00251***	-0.00209***	-0.00204***	-0.00211***					
	(-3.15)	(-3.67)	(-3.06)	(-2.98)	(-3.08)					
Turnover	-0.0000581***	-0.0000591***	-0.0000573***	-0.0000533***	-0.0000574***					
	(-4.58)	(-4.66)	(-4.52)	(-4.21)	(-4.53)					
Bias score						-0.000531***	-0.000654***	-0.000555***	-0.000487***	-0.000562***
						(-6.61)	(-7.99)	(-6.89)	(-6.03)	(-6.93)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,374,607	1,374,607	1,374,607	1,374,607	1,374,607	1,374,607	1,374,607	1,374,607	1,374,607	1,374,607
Adj R^2	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199

Table 6: Are arbitrageurs less biased?

This table reports the pooled regression estimates of weekly portfolio returns on the interactions between arbitrage related variables and behavioral bias related variables.

$$portfolio\ return_{i,t+1} = \alpha_{i,t} + \beta_{1i,t} \times arbitraguer_{i,t} + \beta_{2i,t} \times noise\ trader_{i,t} + \beta_{3i,t} \times unbiased_{i,t} + \beta_{4i,t} \times biased_{i,t} + \beta_{5i,t} \times arbitraguer_{i,t} \times unbiased_{i,t} + \beta_{6i,t} \times noise\ trader_{i,t} \times unbiased_{i,t} + controls + \epsilon_{i,t}$$

We control for both time fixed effect and trader fixed effect; all standard errors are clustered at trader level. For column (1) and (2), *arbitrageur* and *noise trader* are dummies when certain traders fall into the top and bottom 20% on arbitrage score, while *biased* and *unbiased* are dummies when certain traders fall into the top and bottom 20% on composite bias index. Similarly, column (3) and (4) report the same regressions on the top and bottom 30% cutoffs, and the top and bottom 40% cutoffs for column (5) and (6). The coefficients on the interaction terms further support the previous conclusion that behavioral biases influence arbitrageurs more than noise traders. t-statistics are reported in parentheses and the superscripts of *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	Market adjusted trading implied return (week)							
	20-80 cutoff		33-66 cutoff		40-60 cutoff		score value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
arbitrageur	0.00900***	0.00832***	0.00527***	0.00455***	0.00407***	0.00331***		
	(16.19)	(14.65)	(11.45)	(9.34)	(8.64)	(6.51)		
noise trader	0.000454	0.000408	-0.000925**	-0.00109**	-0.00143***	-0.00167***		
	(0.94)	(0.83)	(-2.14)	(-2.39)	(-3.15)	(-3.44)		
unbiased	0.00190***	0.000931*	0.000552	-0.000513	0.000250	-0.000862*		
	(3.51)	(1.68)	(1.22)	(-1.05)	(0.56)	(-1.73)		
biased	-0.00288***	-0.00289***	-0.00266***	-0.00279***	-0.00275***	-0.00295***		
	(-5.67)	(-5.52)	(-6.09)	(-5.82)	(-6.38)	(-5.91)		
arbitrage score							0.000109***	0.000223***
							(14.29)	(6.86)
bias score							-0.000531***	-0.000425***
							(-6.61)	(-5.15)
arbitrageur x unbiased		0.00870***		0.00457***		0.00349***		
		(4.77)		(4.54)		(4.13)		
noise trader x biased		0.00213		0.00176*		0.00157*		
		(1.15)		(1.78)		(1.86)		
arbitrage score *bias index								-0.00000808***
								(-3.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,037,878	2,037,878	2,037,878	2,037,878	2,037,878	2,037,878	1,374,607	1,374,607
Adj R^2	0.196	0.196	0.196	0.196	0.196	0.196	0.199	0.199

Table 7: The persistency of arbitrage trading

This table reports the transition matrix of the five groups of traders. Each cell indicates the weekly transition rate from one group to the other.

$$transition\ rate_{ij} = \frac{p_{ij}}{p_i}$$

The vertical number refers to the group that the trader belongs in the past week, while the horizontal number represents the group that the trader turn to in the new week. The probability that a noise trader still trades as a noise trader next week is 0.89, and the probability that an arbitrageur still trades as an arbitrageur next week is 0.84.

From/To	1 (noise trader)	2	3	4	5 (arbitrageur)
1 (noise trader)	**0.890338**	0.069912	0.022043	0.0107	0.007364
2	0.074994	0.787888	0.091449	0.02282	0.01613
3	0.026325	0.080389	0.7578	0.093299	0.026446
4	0.017753	0.020065	0.081886	0.773302	0.086815
5 (arbitrageur)	0.017904	0.017298	0.020504	0.071456	**0.838118**

Table 8: Account-level characteristics of arbitrageurs

This table reports the account level characteristics of arbitrageurs. *AS_count* measures the frequency that a certain trader is classified as an "arbitrageur".

$$AS\_count_i = \frac{number\ of\ times\ trader\ i\ trades\ as\ arbitrageur}{number\ of\ times\ trader\ i\ trades}$$

All traders are sorted into five groups by *AS_count* every week. Average volume is the mean weekly trading volume in Indian rupee. Average balance is the mean portfolio balance at week end in Indian rupee. Number of currencies held is the average number of currencies held in the portfolio at ween end. Bias score is the average weekly bias index level based on the trading behavior in the past quarter.
Traders who arbitrage more frequently tend to have higher trading volume and lower account balance, held less coins, and suffer higher level of behavioral biases.

rank	**AS_count**	# of traders	Average volume	Average balance (in thousands)	# of currencies held	Average bias index
1	0.029807	97,448	44495.34	1070.22	3.241920	12.100831
2	0.300480	19,127	87210.60	113.09	3.095068	13.040334
3	0.499553	14,767	112922.71	53.33	3.023993	13.572277
4	0.700784	10,011	133607.54	35.44	2.977412	13.902798
5	0.952643	14,584	135967.13	16.64	2.645915	13.895377

Table 9: Robustness check: high intensity arbitrage score

This table reports the double sort and regression results of an alternative arbitrage measure: high intensity arbitrage score. The high intensity arbitrage score only takes the weeks with high level of arbitrage indices within 25th and beyond 75th percentiles into consideration. Panel A shows the average market adjusted portfolio return independently sorted by the high intensity arbitrage score and the composite bias index. t-statistics are reported in parentheses. Panel B shows the pooled regression estimates of market adjusted portfolio return on high-intensity arbitrage activities. We control for both time fixed effect and trader fixed effect, all standard errors are clustered at trader level.

Panel A: Double sort by high-intensity arbitrage score and bias index

TIR (%)	rank_bs	1	2	3	4	5	5-1
rank_as (high intensity)							
1		2.3749	1.989397	2.102398	1.896075	2.228195	-0.14671 (-4.91)
2		2.597261	2.450767	2.610604	2.549753	2.616108	0.018847 (4.15)
3		2.745825	3.100044	2.996733	2.958515	2.795121	0.049296 (6.01)
4		3.633987	3.424685	3.448776	3.333374	2.938723	-0.69526 (-8.37)
5		5.112524	4.465109	4.108666	3.97047	3.754971	-1.35755 (-9.23)
5-1		2.737623 (12.20)	2.475712 (13.27)	2.006267 (12.24)	2.074395 (9.01)	1.526776 (8.52)	

Panel B: Pooled regression for high intensity arbitrage score

	Market adjusted trading implied return (week)				
	(1)	(2)	(3)	(4)	(5)
ASH	0.0000940***			0.000110***	0.000109***
	(15.97)			(14.36)	(14.29)
rank_ash		0.0115***			
		(12.99)			
arbitrageur			0.00874***		
			(15.77)		
noise trader			0.000677		
			(1.40)		
DOX				-0.0000786***	

				(-3.07)	
DE				-0.000465	
				(-0.47)	
LP				-0.00215***	
				(-3.15)	
Turnover				-0.0000581***	
				(-4.58)	
Bias score					-0.000531***
					(-6.61)
Controls	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
N	2,037,878	2,037,878	2,037,878	1,374,607	1,374,607
Adj R^2	0.196	0.196	0.196	0.199	0.199

Table 10: Robustness check: trading fee adjusted portfolio returns

This table reports the the double sort and regression results of an alternative portfolio return measure: trading fee adjusted portfolio return. Trading fee adjusted return equals to the weekly trading implied portfolio return minus the total trading fee paid in the past week (in INR) scaled by account balance. Panel A shows the average fee adjusted portfolio return independently sorted by arbitrage score and the composite bias index. t-statistics are reported in parentheses. Panel B shows the pooled regression estimates of fee adjusted portfolio return on arbitrage activities. We control for both time fixed effect and trader fixed effect, all standard errors are clustered at trader level.

Panel A: trading fee adjusted returns sorted by arbitrage score and composite bias index

TIR (%)	rank_bs	1	2	3	4	5	5-1
rank_as							
1		3.983122	3.635735	3.863793	3.748669	4.247263	0.264141 (1.37)
2		3.91324	4.142534	4.202668	4.294605	4.145915	0.232675 (1.55)
3		4.348936	4.652335	4.665305	4.747957	4.360494	0.011558 (0.08)
4		4.762729	4.698924	4.975169	4.774292	4.506375	-0.25635 (-1.88)
5		6.068174	5.412296	5.03006	4.892404	4.58701	-1.48116 (-8.96)
5-1		2.085053 (12.38)	1.776561 (10.99)	1.166267 (7.75)	1.143735 (7.21)	0.339748 (1.79)	

Panel B: Panel regressions on trading fee adjusted portfolio return

	Trading fee adjusted trading implied return (week)				
	(1)	(2)	(3)	(4)	(5)
AS	0.0000883***			0.000113***	0.000113***
	(14.66)			(14.51)	(14.42)
rank_as		0.0112***			
		(12.39)			
arbitrageur			0.00902***		
			(15.97)		
noise trader			0.000998**		
			(2.01)		
DOX				-0.0000980***	
				(-3.75)	
DE				-0.000639	
				(-0.63)	
LP				-0.00147**	

				(-2.10)	
Turnover				-0.0000576***	
				(-4.47)	
Bias score					-0.000490***
					(-6.00)
Controls	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
N	2,037,878	2,037,878	2,037,878	1,374,607	1,374,607
Adj R^2	0.245	0.245	0.245	0.250	0.250

Table 11: Robustness check: alternative coin samples

This table reports the pooled regression estimates of weekly portfolio returns on arbitrage-related variables on alternative cryptocurrency samples: top 10 currencies, top 20 currencies and the sample excluding the 20\% least traded currencies. In column (3), (6) and (9), only coefficients on interaction terms are reported, and the dummy variables are calculated using the 20-80 cutoffs. We control for both time fixed effect and trader fixed effect, all standard errors are clustered at trader level. t-statistics are reported in parentheses and the superscripts of *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	Market adjusted trading implied return								
	Top 10 coins			Top 20 coins			Bottom 20% excluded		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AS	0.0000883***	0.0000882***		0.0000883***	0.0000882***		0.000124***	0.000122***	
	(13.64)	(13.65)		(13.64)	(13.65)		(9.59)	(9.45)	
DOX	-0.0000577***			-0.0000577***			0.00000877		
	(-3.26)			(-3.26)			(0.17)		
DE	-0.000779			-0.000779			0.00448**		
	(-1.11)			(-1.11)			(2.42)		
LP	-0.00160***			-0.00160***			-0.00202		
	(-3.20)			(-3.20)			(-1.52)		
Turnover	-0.0000241***			-0.0000241***			-0.000108***		
	(-2.77)			(-2.77)			(-4.34)		
Bias score		-0.000375***			-0.000375***			-0.000135	
		(-6.50)			(-6.50)			(-0.83)	
arbitrageur x unbiased			0.00415***			0.00420*			0.00433
			(3.11)			(1.74)			(1.31)
noise trader x biased			0.000484			0.00209			0.00332
			(0.41)			(0.77)			(0.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,365,357	1,365,357	1,976,674	1,365,357	1,365,357	1,365,357	1,982,891	1,982,891	2,061,877
Adj R^2	0.189	0.189	0.184	0.189	0.189	0.189	0.206	0.206	0.189

Appendix A: Variable Description

Panel A: Variables in Trades files

Fields	Desc	Format
Market	Trading Pair example BTCINR USDTINR	Char
Price	Traded Price	Num
Volume	Trade Volume (units)	Num
Trade Date	Transaction date	Date
Ask Order ID	Corresponding order ID for seller	Num
Bid Order ID	Corresponding order ID for buyer	Num
Ask Customer ID	Seller customer ID	Char
Bid Customer ID	Buyer customer ID	Char
Trade Volume	Price*Volume	Num
Bid Fee Paid	Fee paid by buyer	Num
Ask Fee Paid	Fee paid by seller	Num
Currency for bid fee	Currency in which fee is paid by buyer	Char
Currency for ask fee	Currency in which fee is paid by seller	Char

Panel B: Variables in Desposit and Withdrawal files

Fields	Desc	Format
Direction	Deposit or Withdraw	Char
Currency	Currency example BTC INR	Char
Amount	Amount of deposit or withdrawal	Num
Customer ID	Customer ID	Char
Created Date	Transaction Datetime	Date

Appendix B: Double sorting results by arbitrage activity and composite behavioral bias index

Panel A: arbitrage score sorted by arbitrage score and composite bias index

Arbitrage score	rank_bs	1	2	3	4	5	5-1
rank_as							
1		0.118949	0.13153	0.138025	0.144651	0.14953	0.030581 (45.75)
2		0.592084	0.598356	0.608135	0.622649	0.639219	0.047135 (32.83)
3		1.722245	1.764835	1.800227	1.83603	1.871983	0.149738 (38.29)
4		6.239198	6.115719	6.215579	6.468665	6.717655	0.478457 (15.53)
5		81.00887	77.11025	70.53497	70.90639	75.69606	-5.31281 (-15.82)
5-1		80.88992 (281.21)	76.97872 (262.42)	70.39694 (291.48)	70.76174 (360.00)	75.54653 (436.24)	

Panel B: composite bias index sorted by arbitrage score and composite bias index

Bias index	rank_bs	1	2	3	4	5	5-1
rank_as							
1		7.555294	10.83056	12.7397	14.49122	16.84287	9.287575 (1170.45)
2		7.823709	10.90089	12.76463	14.51004	16.82891	9.005199 (1390.71)
3		7.921212	10.96244	12.80903	14.54808	16.87898	8.957769 (1458.87)
4		7.864997	11.01227	12.85876	14.57435	16.90498	9.039985 (1467.73)
5		7.645066	10.97689	12.87561	14.58004	16.98705	9.341981 (1475.51)
5-1		0.089772 (12.66)	0.14633 (40.39)	0.135907 (43.86)	0.088813 (29.74)	0.144178 (19.85)	

Panel C: portfolio balance sorted by arbitrage score and composite bias index

log(balance)	rank_bs	1	2	3	4	5	5-1
rank_as							
1		11.6641	11.51142	11.35289	11.23703	11.09925	-0.56485 (-47.04)
2		10.75889	10.82754	10.70379	10.651	10.5768	-0.18209 (-18.95)
3		10.23677	10.38403	10.34915	10.31166	10.24612	0.009345 (1.03)
4		9.591178	9.865939	9.964541	9.962744	9.824524	0.233346 (25.18)
5		7.05286	7.46779	8.019727	8.357537	8.268558	1.215698 (97.65)
5-1		-4.61124 (-387.76)	-4.04363 (-318.45)	-3.33317 (-282.22)	-2.8795 (-250.58)	-2.83069 (-225.38)	

Panel D: trade volume sorted by arbitrage score and composite bias index

log(volume)	rank_bs	1	2	3	4	5	5-1
rank_as							
1		3.03333	3.597948	3.79918	3.824588	3.919732	0.886402 (29.75)
2		3.845836	4.438678	4.479017	4.479763	4.491174	0.645338 (26.28)
3		4.332451	5.022102	5.184375	5.184599	5.068575	0.736124 (31.82)
4		4.690789	5.388102	5.819787	5.918322	5.747588	1.056799 (46.07)
5		4.082989	4.45433	5.214114	5.731975	5.738123	1.655135 (72.23)
5-1		1.049659 (47.81)	0.856382 (33.64)	1.414934 (57.76)	1.907387 (73.00)	1.818391 (59.61)	